Transportation Research Part A 111 (2018) 187–198

Contents lists available at ScienceDirect

Transportation Research Part A

journal homepage: www.elsevier.com/locate/tra

Cruising and on-street parking pricing: A difference-in-difference analysis of measured parking search time and distance in San Francisco

Farzad Alemi[a,*], Caroline Rodier[a], Christiana Drake[b]

[a] Institute of Transportation Studies, University of California, Davis, 1715 Tilia Street, Room 1149, Davis 95616, CA, United States
[b] Department of Statistics, University of California, Davis, 4101 Mathematical Sciences, One Shield Avenue, Davis 95616, CA, United States

ARTICLE INFO

Keywords:
Cruising
Parking pricing
Parking search time
Parking search distance
Difference-in-difference
SF*park*

ABSTRACT

When on-street parking is scarce, the cost of parking includes the extra time and fuel spent searching for a parking space (or cruising). Cruising also unnecessarily contributes to local congestion, vehicle emissions, air pollution, and climate change. The theoretical literature shows that these social costs can be reduced, or even eliminated, if high-quality information on the demand for and supply of parking is used to set parking prices at optimal levels. Not surprisingly, cities plagued by parking shortages, congested streets, and limited financial resources are interested in parking policies that reduce cruising and improve the efficient use of their existing parking and roadway infrastructure. The current study sheds light on the effect of the San Francisco parking pricing program (known as SF*park*) on curbside parking search time and distance in urban neighborhoods on non-commuter parking. The study differs from previous empirical evaluations of similar parking pricing programs in its use of direct field measurements of parking search time and distance, rather than simulated data or proxy variables, such as parking availability. We use generalized mixed effect difference-in-difference models with data collected before and after the implementation of SF*park* in both treatment and control areas to estimates effects of the San Francisco smart parking project, most importantly the demand responsive parking pricing scheme. The models control for time effects by using data from a separate control area, as opposed to using variables such as block face parking price and employment. The results suggest a significant reduction in average parking search time and distance due to SF*park*. Average parking search time and distance declines by approximately 15% and 12%, respectively, from the control to the treatment areas.

1. Introduction

When on-street parking is scarce, the cost of parking includes the extra time and fuel spent searching for a parking space (or cruising). Cruising also unnecessarily contributes to local congestion, vehicle emissions, air pollution, and climate change. In urban neighborhoods, these costs may be significant: average parking search times can range from 3.5 min to 14 min, and as much as 8% to 74% of traffic can be attributed to cruising (Shoup, 2006). The theoretical literature shows that these social costs can be reduced, or even eliminated, if high quality information on the demand for and supply of parking is used to set parking prices at optimal levels (Anderson and de Palma, 2004; Arnott and Inci, 2006; Arnott and Rowse, 1999, 2009).

* Corresponding author.
E-mail addresses: falemi@ucdavis.edu (F. Alemi), cjrodier@ucdavis.edu (C. Rodier), cmdrake@ucdavis.edu (C. Drake).

https://doi.org/10.1016/j.tra.2018.03.007
Received 21 March 2017; Received in revised form 28 February 2018; Accepted 7 March 2018
Available online 21 March 2018
0965-8564/ © 2018 Elsevier Ltd. All rights reserved.

Not surprisingly, cities plagued by parking shortages, congested streets, and limited financial resources are interested in parking policies that reduce cruising and improve the effective use of their existing parking and roadway infrastructure. Most empirical evaluations of non-commuter curbside parking pricing examine effects on parking occupancy (and in some cases double and illegal parking), but not on the time and distance of parking search travel (Chatman and Manville, 2014; Kelly and Clinch, 2009; Ottosson et al., 2013; Pierce and Shoup, 2013). Only two studies empirically examine the effect of parking pricing on the time and distance of parking search travel. Van Ommeren et al. (2012) use self-reported parking search time data and find that average cruising time is only 36 s per trip. This is in the Netherlands where local on-street and off-street parking are consistently priced. Millard-Ball et al. (2014) apply theoretical models calibrated with parking sensor data from the SF*park* pricing program in San Francisco and find that parking pricing significantly impacts the number of city blocks cruised.

The current study sheds light on the effect of SF*park* on non-commuter curbside parking search time and distance in urban neighborhoods. The study differs from previous empirical evaluations of similar parking pricing programs in its use of direct field measurements of parking search time and distance, rather than simulated data or proxy variables, such as parking availability. We use generalized mixed effects difference-in-difference models with data collected before and after the implementation of SF*park* in both treatment (also called pilot) and control areas. The models control for time effects by using data from a separate control area, as opposed to using variables such as block face parking price and employment.

1.1. Background

SF*park* was implemented in eight neighborhoods in the city of San Francisco (Fillmore, Downtown, South Embarcadero, Mission, Civic Center, Marina, Fisherman's Wharf, and Port of San Francisco), as indicated in Fig. 1 below. These areas encompass approximately 7000 on-street parking spaces (about 25 percent of city's total) and 12,250 off-street parking spaces located in parking garages and one parking lot. Magnetic parking sensors, installed in on-street parking spaces, capture and transmit parking occupancy data. New parking meter technology allows payment by credit cards and remote payment (the previous meters required coins). The one to two-hour parking time limits were also relaxed. Sensors and meters wirelessly transmit data to the San Francisco Municipal Transportation Agency (SFMTA) enabling monitoring of occupancy levels.

SFMTA monitored average parking occupancy over a six-week period by block, by three time periods (morning, mid-day, and afternoon), and for weekdays and weekend days. SF*park* began to charge parking fees on Sundays during the pilot program using a similar pricing structure as weekdays and Saturdays (even during evening hours); however, effective July 2014, the operation of parking meters was stopped on Sundays for most of the on-street metered parking spaces. If observed average occupancy drops below the 60% target average occupancy, then rates decrease by as much as 50 cents per hour. If observed average vehicle occupancy exceeds the 80% target average occupancy, then rates increase by 25 cents per hour. The minimum hourly meter rate is 25 cents per

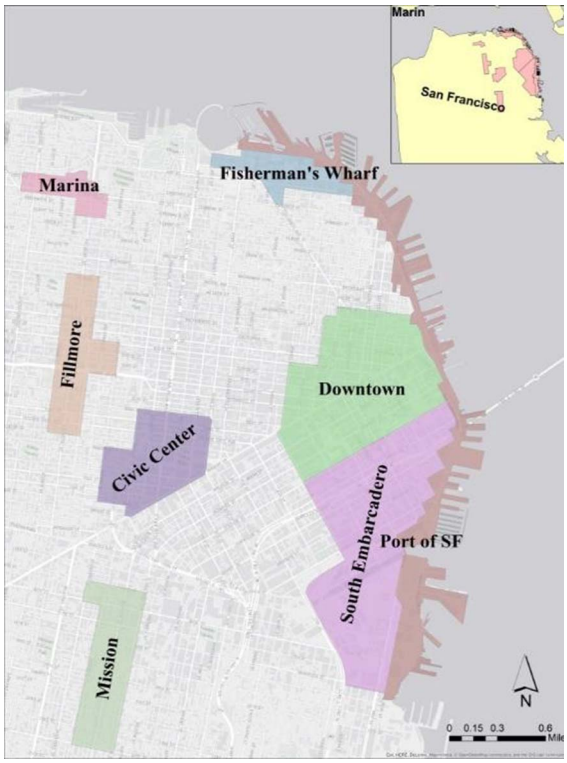

Fig. 1. SF*park* neighborhoods.

hour, and the maximum is 6 dollars per hour. Similar to on-street parking, price of off-street parking spaces located in different city owned garages and one parking lot was also subjected to change in response to demand variation.

1.2. Experimental design

The evaluation of SF*park* employs a quasi-experimental design. The samples were collected in both the control and the pilot areas, before and after, implementation of the pilot in the spring of 2011 (see Fig. 2 below). Fig. 3 illustrates a simplified impact of hypothetical time effects in the control and pilot areas and intervention effects in the pilot area. In Fig. 3, solid lines represent observed data. Over time, economic, demographic changes, and impacts of other enacted policies (e.g. increasing transit services) may confound the effect of the pilot (see "Time Effect" in Fig. 3). Data collected in control areas measure changes over time that may confound the analysis. For example, an economic decline or sharp rise in gas prices may result in reduced traffic and congestion during the before or after data collection period. Fig. 3 shows how the effect of the pilot would be overestimated, if this time effect was not controlled. The opposite is also true. For example, a significant improvement in the local economy may spur additional traffic and congestion, which may have been the case over the 2011 and 2013 period in San Francisco. If the analysis does not control for the time effect, then the positive impact on traffic and congestion may be masked.

SFMTA carefully selected control areas to minimize differences in key attributes relative to pilot areas for the evaluation of SF*park*. However, identifying control and test (or pilot) areas in an actual city is challenging and it is possible that the unique nature of each neighborhood (e.g., population, employment, and vehicle ownership) limits the comparison of time effects. Millard-Ball et al. (2014) note that control areas of Richmond and Union are characterized by a central commercial area surrounded by residential areas and may be more similar to the pilot areas of Marina and Fillmore neighborhoods than the central business districts of Civic Center, Downtown, and South Embarcadero. However, the authors estimated their models with and without these central business districts (i.e., Civic Center, Downtown, and South Embarcadero), but found no significant differences in the results. In addition, the Union control area is close to the Marina pilot area, which may be subjected to spillover effects of the experiment.

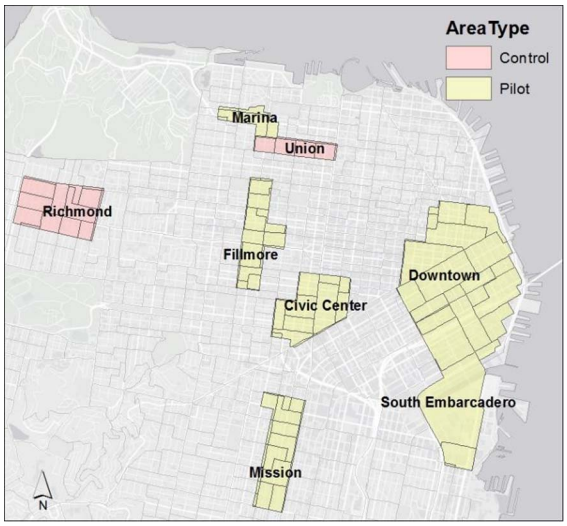

Fig. 2. SF*park* pilot and control areas.

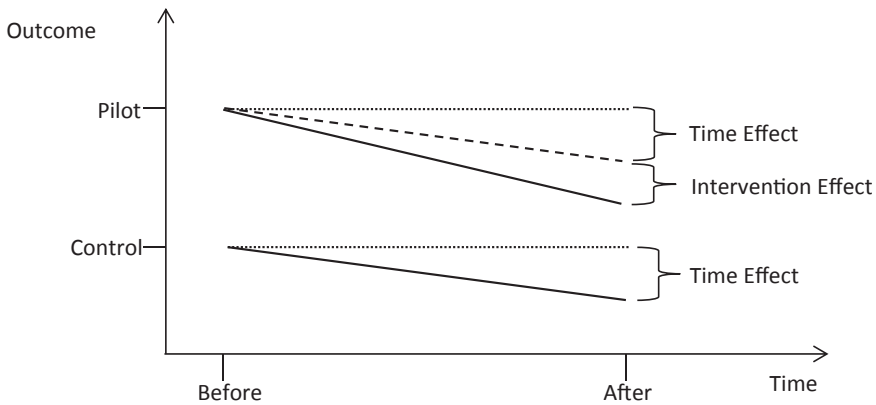

Fig. 3. Hypothetical illustration of possible time and intervention effect in the control and pilot areas.

2. Literature review

As described by (Marsden, 2006), empirical evaluations of the effect of parking pricing have focused largely on commuter parking. Very little literature looks at the effect of parking pricing on non-commuter travel, and all these studies use stated preference surveys to evaluate hypothetical pricing charges (Bain, 2002; Hensher and King, 2001; Shiftan, 2002). In this literature review, we compare the current study to studies that are most relevant: those that use observed or reported data from implemented parking pricing programs, focus on non-commuter curbside parking in urban neighborhoods, and employ statistical analyses that control for confounding variables.

As discussed above, lacking funds to maintain and expand transportation infrastructure, cities and metropolitan regions in the U.S. are increasingly interested in pricing policies that improve the efficiency of their existing infrastructure and, perhaps, raise funds for its maintenance. In response, the U.S. Federal Department of Transportation provided significant funding to implement pricing demonstration projects in cities throughout the U.S. as part of the Urban Partnership Agreement (FHWA, 2014b). The Agreement required that cities that accept demonstration funds must also collect data for use by an external team that would evaluate the effectiveness of their projects. Two cities, San Francisco, and Seattle, implemented demand-responsive parking pricing pilot programs as part of the Agreement. Four of the six studies examined in this literature review used data collected from these two parking pricing pilots. The current study is part of the Federal Highway Administrations evaluation of the SF*park* program (FHWA, 2014a). SFMTA generated descriptive statistics, using the same data used in this study, for their evaluation of SF*park* (SFMTA, 2014b). The analysis did not include control variables and thus it is not included in this literature review.

Table 1 summarizes key elements of the comparable literature as well as the current study. Two studies examine fixed or flat on-street parking pricing programs: one in Dublin, Ireland (Kelly and Clinch, 2009) and another in the Netherlands (Van Ommeren et al., 2012). Four studies evaluate demand responsive on-street parking programs (i.e., parking pricing is adjusted to ensure parking availability over a specified geographic area and time period): one in Seattle (Ottosson et al., 2013) and the rest in San Francisco (SF*park*) (Pierce and Shoup 2013; Millard-Ball et al., 2014; Chatman and Manville 2014).

All the studies use equivalent samples collected before and after the implementation of parking pricing programs. The exception is Van Ommeren et al. (2012) who use repeated responses from travel surveys administered to different participants over a period of three years. Two studies (Chatman and Manville, 2014; Millard-Ball et al., 2014) and the current study also collect data from control areas before and after the implementation of the program. All studies employ statistical analyses that control for factors that may confound the price or program effect, and also control for time of day and day of the week. In the studies that did not include control areas, confounding variables such as, socio-economic variables are included directly in the model. Over time, many factors could confound the analysis of the treatment effect; it may be difficult to accurately measure and completely represent them in statistical analyses. The studies that do employ control areas assume that both the treatment and the control areas respond similarly to changes in socio-economic variables that may confound the analysis. This assumption may not always hold.

The dependent variable in most of the studies is average parking occupancy for a city block; the exception is Kelly and Clinch (2009) who use the parking pricing test area. Chatman and Manville (2014) also develop models for many dependent variables other than average parking occupancy, including parking availability, duration, and turnover rates, as well as double and illegal parking. In general, a decrease in average parking occupancy, double parking, and/or illegal parking, or an increase in parking availability, duration, and/or turnover, suggests a decline in cruising. However, these dependent variables do not allow us to test the significance of the relationships or the direction and magnitude of the change. Two of the studies use dependent variables that explicitly address cruising. Van Ommeren et al. (2012) use parking search time for non-commute trips and Millard-Ball et al. (2014) use number of blocks cruised. Cruising distance and time (in treatment and control areas) is the dependent variable in the current study.

Average vehicle occupancy is estimated with parking meter data in two studies (Kelley and Clinch, 2009 and Ottosson et al., 2013), with parking sensor data in two studies (Pierce and Shoup, 2013; Millard-Ball et al., 2014), and with field survey data in Chatman and Manville (2014) and in the current study. Meter transaction and sensor data is less costly to gather and thus should provide a more comprehensive representation of parking events both temporally and spatially; however, the quality of the data is subject to frequent operational failures and often requires intense data cleaning. The cost of manual surveys can limit sample size, and thus affect how well the sample represents the treatment area. The data may also be subject to surveyor error and bias.

Millard-Ball et al. (2014) use parking sensor data to calibrate theoretical models that simulated average vehicle occupancy and cruising and then used the simulated data to estimate regression ordinary least square and negative binomial models. Simulated data lacks the realism of observed data, but can be a very effective way to derive secondary outcomes from data that are available.

Van Ommeren et al. (2012) use self-reported trip parking search time from the Dutch National Travel Survey over a three-year period with a large sample size. Self-reported data may be subject to recall error. Travel survey data is costly to gather and often suffers from non-response bias.

In the current study, parking search time and distance data are gathered by bicyclists moving with roadway traffic on pre-determined routes. This data collection approach ensures the ability to replicate parking search measurements consistently over time. On the other hand, the samples may not truly represent actual parking search behavior because actual parking search travel may begin and end over greater distances and time, depending on the availability of parking and/or travellers' willingness to walk longer distances to their destination.

The use of block-level average vehicle occupancy as the dependent variable (and other block-level variables) allows for the inclusion of parking pricing as an independent variable at the geographic unit of analysis at which it parking price changes. Practically, this allows direct testing of the significance of the price variable and/or comparisons of estimated price elasticity of demand for on-street parking. In the current study, the indicator for pilot or control area is the independent variable. If the inclusion

Table 1
Summary of studies that evaluate implemented on-street parking pricing programs.

	Kelly and Clinch (2009)	Van Ommeren et al. (2012)	Ottosson et al. (2013)	Pierce and Shoup (2013)	Millard-Ball et al. (2014)	Chatman and Manville (2014)	Current study
Location	Dublin	Netherlands	Seattle	San Francisco	San Francisco	San Francisco	San Francisco
Parking Pricing	Flat	Flat	Demand-Responsive	Demand-Responsive	Demand-Responsive	Demand-Responsive	Demand-Responsive
Experimental Design	Before & after equivalent test groups	Repeated non-equivalent sample	Before & after equivalent test groups	Before & after equivalent test groups	Before & repeated after equivalent test & control groups	Before & repeated after equivalent test and control groups	Before & after equivalent test and control groups
Data Source	Meter	Travel Survey	Meter	Parking sensor	Parking sensor	Field survey	Field survey
Date Collection Dates	6 weeks in 2000 & 2001	2005–2007	4 weeks in 2010 & 2011	6 weeks before & after price change: 2011–2012	2011–2013	May & October 2011 & May 2012	Spring 2011 & 2013
Sample Size	Not reported	11,425	Not reported	5294	Not Reported	132	221
Method of Analysis	Price elasticity equation	Linear regression	Log-log regression	Price elasticity equation	Regression with simulated data	Linear and log–log regression	Generalized mixed effect
Unit of Analysis	Area	Individual	Block	Block	Block	Block	Area (Route)
Dependent Variable(s)	Average parking occupancy	Parking search time for specific trip	Average parking occupancy	Average parking occupancy	% point change average occupancy outside 60–80% & blocks cruised	Average parking occupancy, availability, duration, turnover; double & illegal	Average parking search time & distance
Independent Variable(s)	Price	Income, parking duration, travel duration, & passengers	Price & neighborhood attributes	Price	Price change frequency	Price	Pilot
Control Variable (s)	Income & inflation, elasticity by time of day & day of week	Area, destination, gender, age, arrival time, year & activity type	Time of day, day of week, unique block effects, & spatial correlation between blocks	Elasticity by location, time of day, day of week, initial price, change size & over time	Area, date, day of week & time of day	Initial price, time of day, day of week, area, weather, & employment	Control; time of day, day of week & area
Findings	Average price elasticity of demand is −0.29 & morning peak most responsive	Low cruising times due its strong parking pricing program	Elasticities for price increase from −0.7 to −0.37; price decrease not significant; higher in AM peak	Average price elasticity is −0.4 & varies by largely time of day and location	Block-level rate changes significantly related to average occupancy and blocks cruised.	Price improves average occupancy not parking availability, duration, turnover, or carpooling	15% reduction in parking search time and 12% reduction parking search distance due to pilot

of the control accurately accounts for the time effect, then the results of this study indicate the impact of the change in prices implemented as in the SF*park* project. More dramatic changes in cruising may result from larger changes in parking prices.

3. Data collection and methodology

3.1. Data collection

SFMTA defined parking search routes in the pilot areas (Marina, Fillmore, Civic Center, Mission, Downtown, and South Embarcadero) and in the control areas (Richmond and Union), as illustrated in Fig. 4 below. Each route had a designated starting point located at a major intersection (shown as green dot in Fig. 4). SFMTA instructed surveyors to bike along the defined routes, stop at the first vacant on-street parking space, and, at that point, record the search time, number of laps traveled to find the parking space, and the meter identification number of the found space. This number relates to a spatial database that allows for calculation of distances. If the surveyor does not find a parking space within 30 min, then the surveyor stops the search and makes note that the search failed. After finding the first available vacant on-street parking or exceeding the 30-min search time, surveyors returned to the route starting point and repeated the above process continuously until the end of a two-hour time period. The survey dataset indicated that approximately 20 different surveyors participated in the data collection effort. SFMTA states that the routes were selected to be replicable, consistent, and easy to understand by the surveyors(SFMTA, 2014a).

Surveyors collected data on bicycles rather than in cars to avoid adding to street congestion; however, SFMTA instructed surveyors to travel with the flow of car traffic and to simulate the behavior of drivers in cruising for parking. In fact, in a congested situation bikes can move through traffic faster than a car and thus, may find a vacant parking space more quickly. This means that data collected by bike might be biased downwards, unless surveyors move with the flow of traffic.

In this study we assume a fixed parking start location and restrict the area where parking can be found, which is likely not truly representative of actual parking search behavior, but it does allow for consistent measures of parking search time to be collected over time. After discussions with SFMTA, the research team decided to exclude data from the Mission pilot area. Extensive construction in the Mission pilot area over the course of the data collection period resulted in minimal implementation of SF*park*. As a result, the Mission area could not considered be a true treatment area.

The parking search routes included 62 blocks (127 block faces) and 1150 spaces (excluding Mission). Table 2 describes the share of the parking spaces included in the parking search routes relative to the total number of parking spaces in the control and the pilot areas. This share ranges from 11% to 60%. In each pilot and control area, surveyors collected data (when parking fees applied) on weekdays (Tuesday, Wednesday, or Thursday) and weekends (Saturday and Sunday) by time period (8:00 to 10:00 a.m., noon to 2:00p.m., 4:00 to 6:00p.m., 8:00 to 10:00p.m., and 10:00p.m. to 12:00 a.m.). Surveys were not scheduled in locations with special events that could distort parking search time data (e.g., during parades, street fairs, street cleaning, or major sporting events).

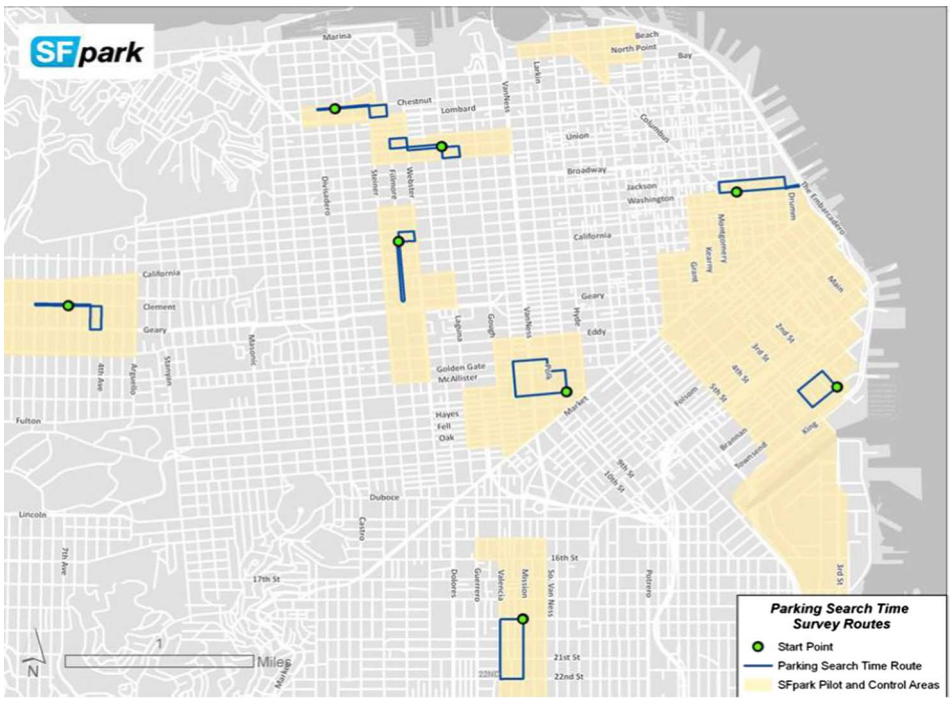

Fig. 4. Parking search time survey routes in citywide context.
Source: SFMTA, 2014a.

Table 2
Percent of parking spaces sampled for the parking search routes of the total parking spaces in the pilot and control areas.

Area	Percentage of total parking spaces in the area
Pilot areas	
Civic center	17
Downtown	37
Fillmore	18
Marina	16
South Embarcadero	11
Control areas	
Richmond	60
Union	40

Surveying in the pilot areas only occurred where and when SF*park* parking pricing existed.

Table 3. describes the change in parking prices in the pilot areas from 2011 to 2013. As discussed earlier, the price was adjusted to ensure average parking occupancy rates of 60% to 80% at the block-level by the different time of day on weekend days or weekdays over a six-week period. Prices changed ten times over the course of the data collection period. A total of 4943 usable single data points were available after SFMTA completed their initial data screening process. In addition, we removed a total number of 13 failed parking search attempts. These attempts were recorded as failed attempts due to unavailability of parking spaces which might have been caused by temporary blockage of multiple parking spaces or part of parking search route (e.g., a freight delivery or an accident), which usually lasts for few minutes. Even though the ratio of failed to successful search attempts is negligible, exclusion of the failed searches may result in biased upward estimation of the search patterns. After removing failed search attempts and the Mission data, the sample size was reduced to 4140 individual data points.

3.2. Methods of analysis

Although there are many thousands of search attempts, these individual searches are not easily incorporated in a statistical model. Survival analysis, the proper method for search times requires independent search times. Models based on correlated survival times such as here are difficult and correlations are challenging to specify. An alternative approach is to use each two-hour block as the observational unit with the number of searches as the outcome variable. Since there was some lag between finding a parking spot and the start of a new search from the designated search start, the actual search times were aggregated and the counts were adjusted for that value. In other words, the number of searches are a function of the time and distance to find a parking space within the search time limit (30 min), return to the starting point of the route, and repeat the search process within a two-hour time period. When parking is scarce, it will take longer to find a parking space and return to the route starting point, than when spaces are plentiful. For example, when parking is limited, it may take 15 min to find a spot and 10 min to return to the route starting point, and thus only about four measurements may be taken in a two-hour time block with an aggregated search time of 60 min. When parking is abundant, it may take five minutes to find a spot and then five minutes to return, and thus as many as 12 measurements may be taken in a two-hour time period with an aggregated search time of 60 min.

As a result, our outcome is a count variable and a suitable statistical model is a Poisson regression model. The parameter of interest is a rate, defined as the number of searches per unit time (or distance). For each data collection time period on each calendar day (noted as i) in each area (noted as j), the count data was adjusted by the actual search time during each two -hour slot by dividing the sum of total number of successful parking search events (noted as y) by the sum of search times or distances of parking search attempts (noted as t). It should also be noted that surveyors did not always search the full two hours allotted.

In addition, data were collected for 10:00p.m. to 12:00 a.m. period occasionally, where SF*park* was in operation mainly to facilitate the demand around AT&T Park. A total number of 23 data points were collected during this period only after implementation of SF*park* and only in South Embarcadero. We removed these 23 observations, since there is not any reference point for

Table 3
Average meter hourly changes in pilot areas from 2011 (before) to 2013 (after).

	Civic Center	Downtown	Fillmore	Marina	South Embarcadero
Weekday					
Morning	−$0.78	$1.19	−$0.09	$0.08	−$0.35
Mid-day	$0.42	$1.92	$0.71	$1.15	$0.70
Afternoon	$0.13	$1.77	$0.42	$1.08	$0.17
Weekend					
Morning	−$1.58	−$0.60	−$0.37	$1.20	−$1.54
Mid-day	−$0.69	$0.29	$1.13	$2.01	−$0.70
Afternoon	−$0.91	$0.05	$1.02	$1.99	−$0.59

Table 4
Descriptive statistics for number of searches and total parking search time and distance for all control and pilot areas ($N_{pilot\text{-}2011}$ = 51, $N_{pilot\text{-}2013}$ = 98, $N_{control\text{-}2011}$ = 30 and $N_{control\text{-}2013}$ = 42).

Area	Year		Mean	Std. Deviation
Control	2011	Number of Searches	15.1	8.3
		Total Search Time (Seconds)	1165.7	1100.2
		Total Search Distance (feet)	10758.0	11077.0
	2013	Number of Searches	18.7	6.1
		Total Search Time (Seconds)	1248.5	859.2
		Total Search Distance (feet)	11936.3	8219.0
Pilot	2011	Number of Searches	19.8	7.0
		Total Search Time (Seconds)	1493.6	1353.5
		Total Search Distance (feet)	12185.7	10821.3
	2013	Number of Searches	19.1	5.7
		Total Search Time (Seconds)	1146.5	979.3
		Total Search Distance (feet)	9631.8	8684.2

data collected during spring 2011. The removal of observations collected during the 10:00 p.m. to 12:00 a.m. period left a sample size of 221 time slots (y_{ij}/t_{ij}) for analysis. In fitting the Poisson model the adjustment in actual search times is achieved by an offset parameter in the regression model.

Descriptive statistics, including the mean, median, and standard deviation of average parking search time and distance (t_{ij}/y_{ij}), for the pilot and control areas in 2011 and 2013 are presented in Table 4. In general, the standard deviation is high for all control areas and all pilot areas. This is because the descriptive statistics in Table 4 do not control for the time of day and day of the week. The model developed and applied in this study does control for these variables. We also conducted chi-square test to determine the significance of the variation introduced by use of different surveyors and results were not significant. The results in Table 4 suggest that average parking search time and parking search distance decreased from 2011 to 2013 in both the pilot and control areas. During this period, citywide population and employment increased by 2% and 7%, respectively (SFMTA, 2014b, p. 29). However, there was also a decline in vehicle ownership per capita (-3%) and VMT (−9%), and an increase in Bay Area Rapid Transit commuter rail ridership (14%) and fuel prices (4%) (SFMTA, 2014b, p. 29). These citywide trends for vehicle travel and the descriptive statistics in Table 4 indicate the need for controlling the time effects from 2011 to 2013 to understand the magnitude of the SF*park* intervention effect.

The median change in parking search time and distance for each area in both the pilot and control are depicted in box-plots on a logarithmic scale in Fig. 5 below. Due to lower sample sizes in each area, the variance is greater than that described for all control

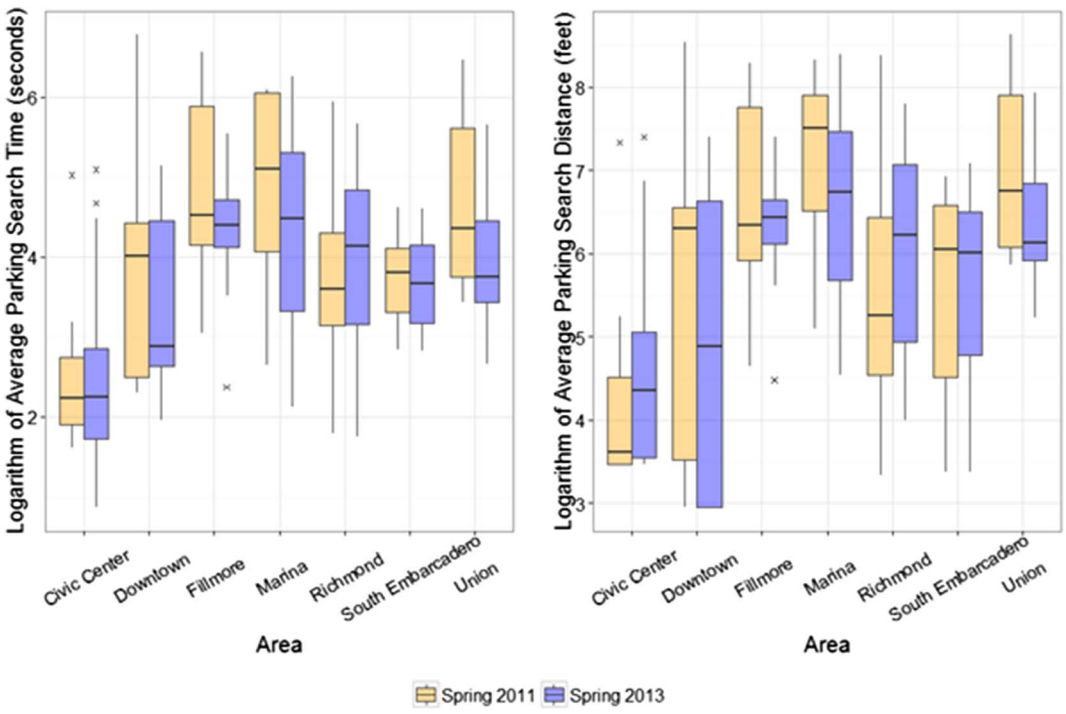

Fig. 5. Average search time and average search distance for each area in the pilot and control (N = 221).

areas and all pilot areas (in Table 4 above). We use the logarithmic scale to adjust for skewness of the data and to illustrate, more clearly, differences among areas by year. From 2011 to 2013 in the two control areas, parking search time and distance increases in Richmond and decreases in Union. In the pilot areas, parking search time decreases somewhat and distance increase in the Civic Center and distance only increases somewhat in the Fillmore. Parking search time and search distance decline in all other pilot areas. Again, these results indicate the need to address the time effect in the analysis.

We examined different methodological approaches to estimate the impact of SF*park* (including demand responsive parking pricing and also introduction of parking pricing on Sundays) on parking search time and distance. While our descriptive statistics primarily use parking search times, the regression models fit for reasons stated above use number of searches adjusted for actual search times, a rate. The inverse of a rate is an average search time. To obtain estimates of search times, we fit Poisson models. These models provide rates and confidence intervals for rates. To obtain estimates of average search times and confidence intervals, we invert the estimates and intervals obtained from our models. During the process of fitting the models, we investigated Poisson regression as well as negative binomial models and employed other Generalized Estimatimation Equation (GEE) models. We present the Poisson regression models because they provided reasonably good fit to the data. Our data did not exhibit extra-Poisson variation or more zeros than would be expected under a Poisson model. Finally, negative binomial models are more sensitive to model misspecification: As discussed by Cameron and Trivedi (2005) the negative binomial model, also, is less robust to misspecification of distributional assumptions.

We present the Poisson models below and discuss the results of our analysis based on this model. Specifically, our model is a generalized mixed effects difference-in-difference model with a Poisson distribution for the outcome variable number of search attempts. The unit of observation is a two-hour time slot at a point in time. In the generalized mixed effect Poisson model, as described in Eq. (1), y_{ij} is the total number of successful parking search events in each area by time of day (two-hour time period) for each calendar day in the pilot and control, and t_{ij} is the sum of the search times (in second) or distances (in feet) for the corresponding successful parking search events in each area.

$$\log[y_{ij}] = \log[t_{ij}] + \beta_0 + b_0 + \beta_p d_p + \beta_{wp} d_{wp} + \beta_{wc} d_{wc} + \beta_1^T X \text{ Which can be re-written as} \quad (1)$$

$$\log[y_{ij}/t_{ij}] = \beta_0 + b_0 + \beta_p d_p + \beta_{wp} d_{wp} + \beta_{wc} d_{wc} + \beta_1^T X \quad (2)$$

$$\text{where } d_p = \begin{cases} 1 & \textit{if pilot area} \\ 0 & \textit{otherwise} \end{cases}, \quad d_{wp} = \begin{cases} 1 & \textit{if 2013 pilot area} \\ 0 & \textit{otherwise} \end{cases}, \quad \textit{and } d_{wc} = \begin{cases} 1 & \textit{if 2013 control area} \\ 0 & \textit{otherwise} \end{cases}.$$

In both the parking search time and distance models, the coefficients from which we estimate the effects of SF*park* are β_p, β_{wp} and β_{wc}. Confounding variables or covariates (x) include the time of day and the day of the week (i.e., weekday versus weekend). Goodness-of-fit tests for separate and combined weekend days indicated that the use of separate weekend days did not improve the model. The intercept is β_0 and the random parking area effect is b_0. Making area a random effect adjusts for heterogeneity between areas and accounts for the fact that observations within an area are typically more similar than observations from different areas and thus likely correlated. The time effect in the pilot areas is measured by β_{wp} (pilot time trend) and in the control areas by β_{wc} (control time trend). Thus, β_{wp}-β_{wc} measures the intervention effect of SF*park*. The pilot group specific effect is denoted by β_p, which controls for initial differences that might exist between pilot and control areas. If β_p is significant, then measured outcomes are different before implementation of the pricing program. Interpretation of this coefficient only makes sense if β_{wp}-$\beta_{wc} = 0$.

4. Results

Table 5 depicts the Poisson model estimates. The estimated coefficients are in rate ratios. In both the parking search time and search distance models, we see that β_p is not significant, and thus the control and pilot areas were comparable.

In the parking search distance model, the estimate for the day of the week variable is found to be significant: number of searches adjusted for actual search distance is approximately doubled during weekends. However, the impact of day of the week is not significant at 0.05 level in the parking search time model. This could be due to greater variability in parking search time rates. Parking search time varies by speed (e.g., if parking search time is equal to 44 s, a surveyors might have traveled 440 feet with a speed of 10 feet/s, or might have traveled 220 feet with a speed of 5 feet/s), which makes it harder to detect a significant effect.

The estimates for the time of day variables are all relative to the 8 to 10 a.m. time period, and indicate a decrease in parking events per unit of time or distance in both the afternoon and evening, while controlling for day of the week and for the same area (see Table 5). This is consistent with the decline in parking hourly rates in three of the five pilot areas over the same period. As parking rates decline, then there should be an increase in parking events per unit of time or distance. The estimates for the control and pilot time trends, in Table 5, show that the number of successful parking events by time or distance units increase in both the control and pilot areas, but more so in pilot areas.

As discussed earlier, the inverse of the dependent variables (number of searches adjusted by time or distance) in these model are equivalent to changes in average parking search time and distance, and thus we can see that they both decrease over time, but, again, more so in the pilot than the control areas. These results indicate the presence of time effects.

In order to control for the identified time effects and isolate the intervention effect of SF*park*, difference-in-differences estimates are developed from the models estimated above (see Table 6). The coefficients for changes in pilot and in control areas for time and distance model are significant at the 0.05 level. These coefficients are the inverse of the dependent variable. The Wald tests indicate that the difference between these coefficients, which is the intervention effect, is significant ($p = 0.03$) for parking search time and

Table 5
Estimated parameters and confidence intervals for the parking search model (N = 221).

Variables	Parking search time			Parking search distance		
	Estimate[a]	Confidence interval		Estimate[a]	Confidence interval	
		2.5%	97.5%		2.5%	97.5%
Pilot Group Specific Effect	1.09*(0.82)* [b]	0.49	2.44	1.30*(0.54)*	0.57	2.94
Control Time Trend	1.21*(0.00)*	1.07	1.36	1.21*(0.00)*	1.07	1.35
Pilot Time Trend	1.42*(0.00)*	1.31	1.54	1.38*(0.00)*	1.27	1.49
Day of the week (reference weekdays)						
Weekend	0.98*(0.48)*	0.91	1.04	1.08*(0.03)*	1.01	1.16
Time of the Day (reference 8–10 am)						
12–2 pm	0.30*(0.00)*	0.28	0.33	0.27*(0.00)*	0.25	0.29
4–6 pm	0.48*(0.00)*	0.44	0.52	0.44*(0.00)*	0.41	0.49
8–10 pm	0.38*(0.00)*	0.35	0.42	0.30*(0.00)*	0.27	0.33
Intercept	0.03*(0.00)*	0.01	0.06	0.00*(0.00)*	0.00	0.01
Log Likelihood	−1645			−2364		
Null-Log Likelihood	−2935			−3745		

[a] All estimates and confidence intervals are reported as rate ratio.
[b] P-values are reported in parenthesis.

Table 6
Average change in parking search time and distance in pilot and control areas.

	Changes in pilot areas	Changes in control areas	Changes caused by SFpark	Confidence int (SFpark effect)		Number of observation
				2.50%	97.50%	
Average parking search time	0.70 **(0.00)**	0.83 **(0.00)**	0.85 **(0.03)**	0.74	0.98	221
Average parking search distance	0.73 **(0.00)**	0.83 **(0.00)**	0.88 (0.07)	0.76	1.01	221

[a] Changes are rate ratios.
[b] The bold P-values are statistically significant at 95% confidence interval.
[c] P-values are reported in parenthesis.

nearly significant (p = 0.07) for parking search distance. The inverse of the coefficients for the change in all pilot areas and in all control areas is taken to transform the estimated change in successful parking search events per unit of time and distance to the estimated change in average parking search time and average parking search distance. The results show that, in pilot areas, the average parking search time and the average parking search distance decreased by about 15% and 12% due to SF*park*.

These results are used to estimate the average total change in 2013 with and without SF*park* by time of day and day type. Average search time ranges from about half a minute to two minutes. These results are lower than those reported by (Shoup, 2006); however, the 3.5–14 min of cruising may be biased upward because researchers usually study cruising where they expect to find it. The morning average search time is closer to the Van Ommeren et al.'s (2012) find of 36 s. As described above, the data collection effort may underestimate total time and distance in order to implement a consistent measure of parking search travel over time. The absolute difference varies by time of day and day type and ranges from 3.2 s to 10.6 s for average parking search time and 50 to 200 feet for average parking search distance (See Table 7).

Further, to estimate the potential societal benefit of SF*park*, we estimate a total reduction of parking search time and search distance for each of the five pilot areas. To do so, we first estimated the number of successful parking events based on the number of available metered spaces in each area and assume a turnover rate of 1 to 3 h for each car with an average parking occupancy in each area (e.g., 60% to 100%). Next, we multiply the number of successful cruising by average changes in parking search time and distance as displayed in Table 7. The results show a total reduction in both parking search time and search distance in each of the pilot neighborhood. For example, in one of the scenarios where we assumed a turnover rate of 1 and average parking occupancy of 80% (the main objective of demand-responsive parking pricing), SF*park* could reduce both daily parking search time and distance by more than 200 h and 2500 miles in the studied pilot areas, respectively.

5. Conclusions

The study describes the effect of a demand-response parking pilot program in San Francisco, known as SF*park*, on both the time and distance of cruising for parking. The effect is evaluated with measured data in pilot and control areas before (2011) and after (2013) the implementation of the pilot. We fit a generalized mixed effects difference-in-difference model on the acquired data,

Table 7
Average search time (sec) and distance (feet) in 2013 with and without SF*park* in the pilot area by time period and weekday/weekend.

Time	2013 without SF*park*		2013 with SF*park*		Total change	
	Time	Distance	Time	Distance	Time	Distance
Weekday						
8–10 AM	35.40	340.36	32.20	286.73	3.2	53.63
12–2 PM	116.69	1267.14	106.37	1067.50	10.32	199.64
4–6 PM	74.17	762.95	67.59	642.75	6.58	120.2
8–10 PM	92.95	1147.07	84.72	966.35	8.23	180.72
Weekend						
8–10 AM	36.28	313.55	33.01	264.14	3.27	49.41
12–2 PM	119.61	1167.31	109.02	983.40	10.59	183.91
4–6 PM	76.02	702.85	69.28	592.11	6.74	110.74
8–10 PM	95.27	1056.70	86.83	890.22	8.44	166.48

controlling for time effects, area effects, time of day, and day of the week. This study differs from previous evaluations of demand-responsive parking programs in two ways. First, it uses direct field measurements of parking search time and distance rather than simulated data or proxy variables such as parking availability, double-parking, and illegal parking. Second, it uses pilot areas as the independent variable and accounts for time effects with data collected from control areas. The results show that SF*park* reduced average parking search time and distance by about 15% and 12%, respectively, in the pilot areas relative to the control areas. In term of the magnitude of reduction, SF*park* could reduce total parking search time and distance by more than 200 h and 2500 miles per day in the pilot areas, which could improve traffic congestion, increase net parking revenues, and reduce GHG emissions. High parking prices and wider application of the SF*park* program could produce larger changes in parking search time and distance.

However, given the pent-up demand for vehicle travel in San Francisco, any reduction in congestion, due to reduced parking search travel caused by SF*park*, is likely to return quickly. The change detected in our analysis suggests improvement in the effective capacity of the streets, but not necessarily reduced congestion, VMT, vehicle emissions, air pollution, and climate change. Parking pricing programs can have a number of effects that could both increase or decrease VMT. If the price of parking is too high for travelers, some may forego trips to the area, travel to other destinations (closer or farther away), and use alternative modes (e.g., transit, walk, or bike). On the other hand, if travel time is lower and the parking price is not too high, then some travelers may make more vehicle trips (with shorter duration) to areas with parking pricing. In addition, lower travel times on streets with parking pricing may encourage more through travel. The balance of these effects could be captured by travel survey data that include a large number of equivalent or non-equivalent samples collected over time. However, the cost of such surveys is likely to be prohibitive. Cell phone data may provide a cost-effective alternative to travel survey data in the future and allow for analysis of the overall travel effects of parking pricing in urban neighborhoods.

Acknowledgement

This paper is based on work performed for Battelle under contract to the U.S. Department of Transportation, contract number DTFH61-06-D-000-7/ORDER 07-T-08002/WP BA07-041. Special thanks go to the following individuals who provided critical data and guidance: Jay Primus and Steph Nelson from the San Francisco Metropolitan Transportation Agency, Allan Greenberg from the Federal Highways Administration, and Carol Zimmerman from Battelle.

References

Anderson, S.P., de Palma, A., 2004. The economics of pricing parking. J. Urban Econ. 55, 1–20.
Arnott, R., Inci, E., 2006. An integrated model of downtown parking and traffic congestion. J. Urban Econ. 60, 418–442.
Arnott, R., Rowse, J., 1999. Modeling parking. J. Urban Econ. 45, 97–124.
Arnott, R., Rowse, J., 2009. Downtown parking in auto city. Region. Sci. Urban Econ. 39, 1–14.
Bain, R., 2002. Improving the quality of city centre parking: will the consumer pay? Traffic Eng. Control 43, 175–179.
Cameron, A.C., Trivedi, P.K., 2005. Micro-Econometrics: Methods and Applications. Cambridge.
Chatman, D.G., Manville, M., 2014. Theory versus implementation in congestion-priced parking: an evaluation of SFpark, 2011–2012. Res. Transp. Econ. 44, 52–60.
FHWA, 2014a. San Francisco Urban Partnership Agreement: National Evaluation Report.
FHWA, 2014b. Urban Partnership Agrrement and Congestion Reduction Demonstration Programs: Lesson Learned on Congestion Pricing from the Seattle and Atlanta Household Travel Behavior Survey. Federal Highway Administration.
Hensher, D.A., King, J., 2001. Parking demand and responsiveness to supply, pricing and location in the Sydney central business district. Transp. Res. Part A 23, 177–196.
Kelly, J.A., Clinch, J.P., 2009. Temporal variance of revealed preference on-street parking price elasticity. Transp. Policy 16, 193–199.
Marsden, G., 2006. The evidence base for parking policies—a review. Transp. Policy 13, 447–457.
Millard-Ball, A., Weinberger, R.R., Hampshire, R.C., 2014. Is the curb 80% full or 20% empty? Assessing the impacts of San Francisco's parking pricing experiment. Transp. Res. Part A: Policy Practice 63, 76–92.
Ottosson, D.B., Chen, C., Wang, T., Lin, H., 2013. The sensitivity of on-street parking demand in response to price changes: a case study in Seattle, WA. Transp. Policy 25, 222–232.
Pierce, G., Shoup, D., 2013. Getting the Prices Right. J. Am. Plan. Assoc. 79, 67–81.
SFMTA, 2014a. SFpark: Parking Search Time Data Guide.

SFMTA, 2014b. SFpark: Pilot Project Evaluation. San Francisco Municipal Transportation Agency, San Francisco.
Shiftan, Y., 2002. The effects of parking pricing and supply on travel patterns to a major business district. In: Stern, E., Salomon, I., Bovy, P.H.L. (Eds.), Travel Behaviour: Spatial Patterns, Congestion and Modelling. Edward Elgar Publishing, Cheltenham, UK., pp. 37–52.
Shoup, D.C., 2006. Cruising for parking. Transp. Policy 13, 479–486.
Van Ommeren, J.N., Wentink, D., Rietveld, P., 2012. Empirical evidence on cruising for parking. Transp. Res. Part A: Policy Pract. 46, 123–130.